Digital Image Processing for the Determination of Dynamic Effects in Roller Bearings

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***Abstract*—Monitoring the functional behaviour of roller bearings during operation offers the potential to detect the bearings wear state early and to forecast possible machine breakdowns. This paper presents an approach to develop a new optical roller slippage measuring method for bearings. Essential for this method is an image derotator combined with a high speed camera. In this paper the analysis of the image information of the roller movement is considered by digital image processing methods such as template matching and neural networks.**

I. Introduction

In most roller bearing applications, operating conditions are such, that there is no relative motion (sliding) between the rolling elements [1]. At least one location in each of the rolling element-raceway contact areas will be the instant center. If during bearing operation no instant center can be found, either at the inner or outer raceway contact, then skidding of the rolling element takes place (fig. 1). Unsteady Skidding motions cause damage at the bearing surfaces. Due to the relative motion, solid body friction occurs. Thereby, during the relative motion of the rolling element and raceway surfaces, a sufficient lubricant-film can not be generated and the surfaces are not completely separated. As a Result, surface damage in terms of smearing occurs [2]. During further operation of the bearing, fatigue and cracks develop on the raceways. Resulting damage affects the operational behaviour and noise emission of bearing significantly as well as bearing breakdown after short operation-time [3]. Up to now, a limited range of slippage measuring methods for bearings exist [3, 4, 5, 6]. Unfortunately, they are complex to apply and only suitable for a small number of bearing types, especially for big-sized bearings (30-60 mm roller diameter) [3, 4]. The majority of bearings in industrial applications have small dimensions, which are difficult to examine with these methods.

In this paper, the development of a novel optical measuring system to identify the dynamic slippage behaviour of roller elements exactly during bearing operation will be presented.

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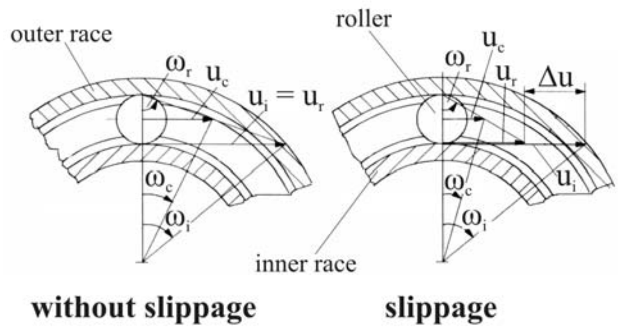

Fig. 1 Bearing velocity arrangement with slippage and without slippage

II. Measuring Principle

The new measuring system includes an image derotator and a high speed camera to monitor the rotary object, e.g. a roller bearing. The principle of the measuring setup is shown in fig. 2. The main component of the derotator is a dove prism. To receive an optimally derotated image, the optical axis of the prism, the rotary axis of its drive and the rotary axis of the object should be identical and the prism should rotate with the half of rotational frequency of the rotating object. The dove prism is located at the centre of a hollow-shafted torque motor that effects the rotary motion.

The applied high speed camera captures 500 images/s at a maximum resolution of 1280 x 1024 pixels. In this experiment the dove prism rotates with half of the rotational frequency of the bearing cage f_c. So it is possible to have a stationary view at the cage and the possibility to observe the rotational movement of the roller elements. The real rotational frequency of the roller elements f_{re} can be determined from these images. To measure the effective roller slippage, the rotational frequency of the raceways has to be considered, too. The rotational frequency of the inner race f_s is measured by a rotary encoder installed close to the bearing shaft. The rolling element frequency f_r can be determined by

$$f_r = \frac{D}{d} \, f_s / 2 \left(1 - \left(d / D\right)^2 \cos^2\left(\alpha\right)\right) \tag{1}$$

The percentage roller slippage will be calculated as

$$\Delta f_r = \frac{f_r - f_{re}}{f_r} \times 100 \tag{2}$$

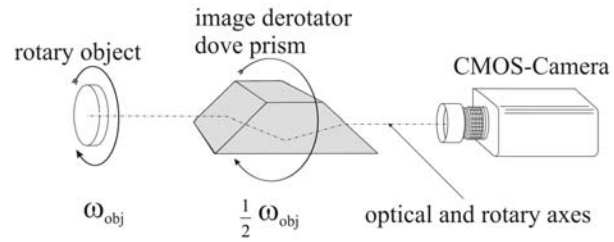

Fig. 2 Principle of measuring setup

III. IMAGE ANALYSIS TECHNIQUE

The frequency of roller elements f_{re} will be determined by tracking the movement of geometric features on the roller elements using sequential images. These images are captured by a high speed camera during bearing rotation (fig. 3).

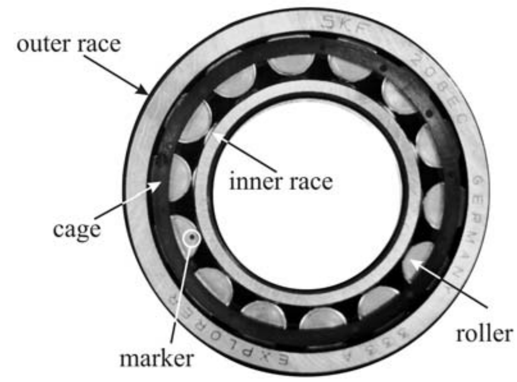

Fig. 3 Image acquisition with a high speed camera

First the contrast, brightness and intensity of the images will be adjusted by using digital image processing techniques. Intensity adjustment is an image enhancement technique that maps an image's intensity values to a new specified range such that certain features will be easier to see.

Some roller elements of the bearing have been marked by laser-induced ablation (fig. 3). The velocity of a feature that is identified on 2 sequential images can easily be obtained by dividing the distance it has covered by the time lag between the 2 images. To track these marks there are several applicable methods. In this work, two different methods, which are suitable for this approach, will be introduced.

A. *Template matching method based on correlation*

A “template” window is selected in the first image of the sequence. In the following images of the sequence, the same template will be searched automatically. Here, the matches of a subimage $w(x, y)$ of the size $J \times K$ will be found within an image $f(x, y)$ of the size $M \times N$ (fig. 4). The subimage will be scrolled over the current image and in each position the correlation between $f(x, y)$ and $w(x, y)$ will be determined as

$$\gamma(x, y) = \frac{\sum_s \sum_t f(s,t) w(x+s, y+t)}{\left\{\sum_s \sum_t \left[f(s,t) - \bar{f}\right]^2 \sum_s \sum_t \left[w(x+s, y+t) - \bar{w}\right]^2\right\}^{\frac{1}{2}}} \tag{3}$$

For x = 0, 1, 2, ..., M-1; y = 0, 1, 2, …, N-1

The sum is taken over the image region where w and f overlap. The maximum of these cross-correlation values within the search window is chosen as the best match.

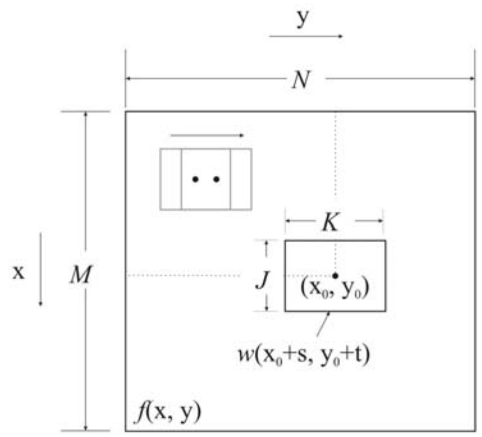

Fig. 4 Arrangement to obtain the correlation of f and w at point (x_0, y_0)

The images, captured by the high speed camera, are correlated with a window around the marker. Fig. 5 shows this window and the correlation result of an experimental setup for the image example (marker) in fig. 3.

The coordinates of the mark center in the image are determined by the maximum value of correlation between the defined template and the real image shape.

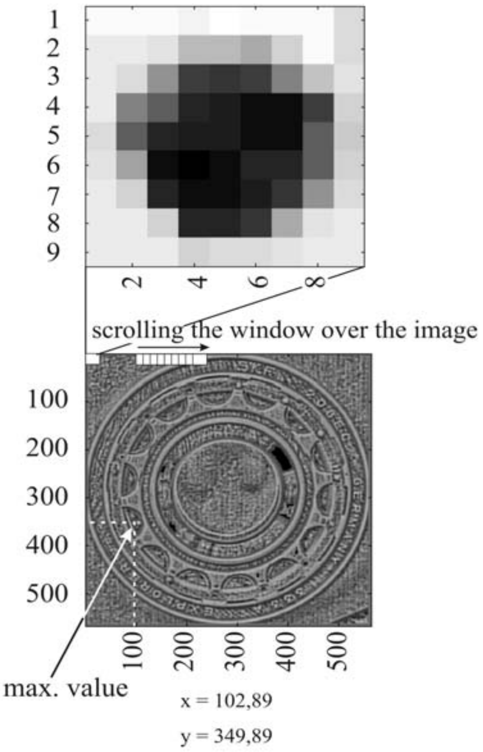

Fig. 5 Example for image scanning and correlation results

This Method is easy to understand and accordingly simple to implement. But the disadvantage of this method is its high demand for computing resources. Additionally, if one image includes a distorted pattern, the true object may not be identified at all.

B. *Neural networks*

Neural network models may also be used for solving pattern recognition problems because of their characteristics, the major one of which can be are summarized as follows [7]:

- robust and resistant to noise
- tolerance to distorted images/patterns (ability to generalize)
- potential for parallel processing
- superior ability to recognize partially occluded or degraded images

Several different types of neural networks have been developed. The Feed-Forward Network with the training algorithm "Backpropagation of Errors" is the most widely used one, especially for pattern recognition problems [8]. This network is commonly known as "Backpropagation network". A Neural Network can be displayed mathematically as a directed graph with neurons as nodes and a connection between them as directed edge. The neurons weight the input signals, connect them and calculate the output signal via a transfer function. The neural network maps the raw input data directly onto the required final output values.

In order to use the neural networks, it is very important to have knowledge about the input data. Especially in image processing problems, there are high-dimensional data sets and the analysis of such an amount of data is very complex to handle. Therefore it is firstly necessary to transform the data into some new representation before training a neural network. This process is named feature extraction and can be regarded as a reduction in dimensionality utilizing a process of variable selection, transformation or mapping which causes some variables to be more meaningful and relevant than others [9]. There are several methods to reduce the amount of data without removing important information like wavelet transformation, e.g. principal component analysis [7] and statistical calculation [10].

In the present case, the problem can be divided into two sections. Firstly object recognition and then localization of the object will be applied. Fig. 6 illustrates this approach.

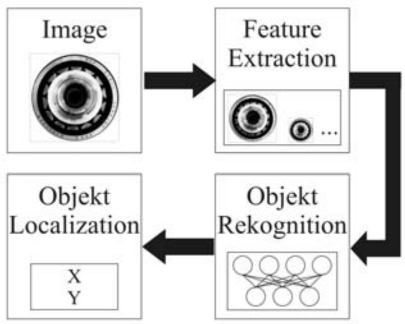

Fig. 6 Approach to identify rotating object information

Firstly, the pixel intensities of the gray scale image will be used and, by applying a transformation-based feature extraction strategy, the input data for the neurons will be prepared. Thereby, the resulting features not only reduce the dimensionality of the input space but also preserve most of the essential information-content of the image. For the recognition of the marker and estimation of its position a backpropagation network will be used. The feature vector is the input data of the network and the position of the marker is its output. Here, the recognition of the marker means to classify between the background and the marker. In this case, the background will be modelled in such way, that the feature vector represents only a single object class and in fact the marker.

IV. CONCLUSION

In this paper a novel optical measuring system for the analysis of the roller slippage is introduced. The outputs of the system are digitalized images which can be interpreted by digital image processing methods. Two different types of these methods, which are suitable for this approach, are described. Additionally the advantages and disadvantages of these methods have been accounted for. The correlation method is already in use and shows good results for image processing and slippage identification. In order to acquire a robust algorithm neural networks will be applied in future works.

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